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Weather Generator Application with Mixed Exponential Distribution Representing Rainfall Intensity

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Adequate and accurate rainfall information is vital in hydrological forecasting, however historical data are sometimes inadequate or nonexistence at location of interest. Stochastic weather generator which is developed based on historical metrological data, is often employed to generate synthetic rainfall series. In this study, the Advanced Weather Generator or AWE-GEN is employed to generate hourly rainfall series in the state of Johor, Malaysia. Within the AWE-GEN, is the Neyman Scott model to assess rainfall series. This study proposed the use of Mixed Exponential distribution in representing rainfall intensity of the Neyman Scott model. AWE-GEN is developed based on meteorological data from period 1975-2015. The model is then used to generate rainfall series separately at two sites within Johor. Generated results were found to be comparable to the historical rainfall series at both sites. Although rainfall distribution at the two sites are influenced by different monsoon winds, the model is able to capture significant statistical characteristics of rainfall behavior at each site. The successful development of this model could be beneficial in addressing issues such as insufficiency of rainfall data at rainfall stations. In addition the model could be employed to generate data as input to various hydrological models.
Keywords: stochastic model, metrological data, rainfall intensity, probability distribution, weather generator.

I. Introduction

Stochastic weather generator is a statistical model of observed weather variables, with variables generally conditioned on the occurrence of precipitation (Fowler et al. (2007), Hashmi et al. (2011)). Such models provide the means to downscale large-scale climate data at both spatial and temporal scales. Over the years, various weather generators have been developed and improvised in order to produce reliable output, for example the Weather Generator (WGEN) (Richardson (1981), Richardson and Wright (1984)), Climate Generator (CLIGEN) (Nicks et al. (1995)) and Long Ashton Research Station-Weather Generator (LARS-WG) (Semenov et al. (2002)) and Advanced Weather Generator (AWE-GEN) (Fatichi et al. (2011)). In general, weather generators put major emphasis on the empirical statistical relationships that maintain the autocorrelation and correlation properties of various variables. Many studies using weather generators produce simulated output at coarse time scales ranging from daily to annual periods (Kilsby et al. (2007)). In view of extreme weather events around the globe such as flooding, output at shorter time scale is preferred in hydrological studies. One of the drawbacks of daily weather generators is that they tend to underestimate monthly and inter-annual variances due to lack of consideration in estimating the low-frequency component of climate variability (Kilsby et al. (2007)). Dubrovský et al. (2004) used a monthly generator (based on first-order autoregressive model) to adjust the low frequency capability based on daily WGEN model. Despite the well simulated results, this model could not capture the inter-annual variability. Wang and Nathan (2007) has introduced the method for the pairing of two different time scales modeled stochastic hydrological time series model. Two resembling time series were produced, one preserves important statistical properties on a finer time scale and another one is on a coarser scale of time. The adjustment is made on a series of finer time scales so that the series is consistent with a series of coarser time scales. The results show that the coupling method is able to produce a series of daily rainy days which preserves some important statistical properties on daily, monthly and yearly scales. Other studies of weather generator (Chen et al. (2011), Furrer and Katz (2008), Keller (2015), Semenov (2008), Wilby et al. (2002)) were also conducted to address problems related to daily weather generator. In addition, Mehan et al. (2017) have compared the performance of different stochastic weather generators for long term climate data simulation. In particular, CLImate GENerator (CLIGEN), Long Ashton Research Station Weather Generator (LARS-WG), and Weather Generators (WeaGETS) were compared in terms of their ability in capturing important statistic features. The observed daily monitoring statistical features and minimum and maximum daily air temperature were well simulated using both CLIGEN and LARS-WG models. These generators can also simulate maximum growth periods and increasing degree days, making them ideal for plant growth simulation. However, WeaGETS model is not quite well in capturing the descriptive statistics, output value distributions, and evaluation of extreme variables. Recent study by Keller et al. (2017) has applied the weather generator for climate downscaling approach over Switzerland. The multi-variate weather generator has been used to downscale future daily weather time-series (precipitation, minimum and maximum temperature). The weather generator was calibrated at the individual stations over a reference period of 30 years (1980–2009) and run under future climate conditions for the A1B Special Report on Emissions Scenarios (SRES) scenario period from 2070 to 2099.

In Malaysia, Hassan and Harun (2013) has applied LARS-WG model to downscale the future daily rainfall at the catchment Kerian in Perak state. Results indicated that daily rainfall was projected to be decreased under A2 SRES scenario. The performance of LARS-WG has also been compared with Statistical Downscaling Model (SDSM) (Hassan et al. (2014)). It was found that SDSM yields a better results compared to LARS-WG, although SDSM slightly underestimated the wet and dry spell lengths. Both models indicate a general increasing trend in the mean daily temperature values (Hassan et al. (2014)). Similarly, an AWE-GEN (Advanced Weather Generator) model, developed by Fatichi et al. (2011), has been applied over Peninsular Malaysia to reproduce a broad range of temporal scales in weather variables from the high-frequency hourly values to the low-frequency inter-annual variability. However, in contrast with the earlier study, this weather generator had projected an increase in extreme rainfall events under Representative Concentration Pathway (RCP) 6.0 scenario (Syafrina et al. (2018)). The results are consistent with Pachauri et al. (2014) in which the studies indicate a positive trend of rainfall over the Malaysia region between 2001 and 2099.

AWE-GEN model (Fatichi et al. (2011), Syafrina et al. (2018)) uses Gamma distribution representing the rainfall intensity. With respect to Malaysia's rainfall scenario, several types of distributions have been employed to represent rainfall intensity and the results varied according to the models being used. For instance, Generalized Pareto has been found to be the best distribution of rainfall intensity in Peninsular Malaysia to model the rainfall intensity (Hassan et al. (2015)). Another study found that Mixed Lognormal distribution was the best distribution model for most of the rain gauge stations in Peninsular Malaysia (Suhaila et al. (2011)). Studies by Abas et al. (2014) and Daud et al. (2016) using Neyman Scott methodology showed that Mixed Exponential was the best distribution to describe the intensity of rainfall in Peninsular Malaysia. Based on the successful use of Mixed Exponential distribution in Malaysia, the main aim of this study is to evaluate the capability of the said distribution in a weather generator, namely AWE-GEN. Since finer resolution rainfall data has many uses in extreme event studies, the study focuses on data at hourly scale. The study site is situated in Johor, Malaysia where the occurrence of flooding is quite frequent. In this paper, the data involved are described in Section 2 while methodology used is in Section 3. Next, the results are discussed in Section 4 and lastly, the conclusion is presented in Section 5.

II. Methodology

Located near the equator, Malaysia experiences a tropical climate with high temperatures and rain all year long. Monsoonal rainfall is becoming more erratic and unpredictable from year to year (Lim and Samah (2004)). Malaysia experiences two monsoon seasons; the southwest monsoon between mid to October and the northeast monsoon from October to March. The east coast of Peninsular Malaysia continues to be affected by the northeast monsoon which brings higher rainfall amount than southwest monsoon. The focus area in this study, Johor is situated in the southeastern part of Peninsular Malaysia and is located between the 1^o20'N and 2^o35'N latitudes. Johor has total land area of 19,210 km^2 and a population of about 3.2 million as of 2010. Johor's rainfall distribution is governed by southwest monsoon (November to February) which brings heavy rain, resulting in frequent flooding occurrences during this period. The average annual rainfall is 2355 mm with average temperature ranging between 25.5^{o}C and 27.8^{o}C.

In this study, the AWE-GEN model is constructed based on 41 years of historical data (1975-2015). The input data required by AWE-GEN are hourly scaled data such as rainfall, temperature, relative humidity and wind speed. Rainfall data were sourced from the Malaysia Drainage and Irrigation Department (DID) while the other meteorological data were sourced from Malaysian Meteorological Department (MMD).

In AWE-GEN model, the proposed Mixed Exponential distribution is fitted to the intensity of rainfall and the intra-annual variability of rainfall is captured by the Neyman-Scott Rectangular Pulses (NSRP) model. Work by Abas et al. (2014) and Norzaida et al. (2016) indicated that the NSRP model is suitable to be used in Malaysia. The proposed model is then used to generate hourly rainfall series separately at two stations within the state of Johor. Simulated results are then compared with the observed data. Figure 1 shows the location of the rainfall stations whereas Table 1 lists the selected stations used in this study. The Mixed Exponential distribution that is associated with NSRP is as in Equation (1) where ξ (light rain) and θ (heavy rain) are the scale parameters, α is the mixing probability parameter; set to a constant, 0.65 following Fadhilah et al. (2008) and x is the hourly rainfall amount. Table 2 gives the definition of each rainfall parameter estimated by NSRP model.

$$f(x) = (\alpha/\xi)e^{-x/\xi} + ((1-\alpha)/\theta)^{-x/\theta} \quad (1)$$

for $x > 0$, $0 \leqslant \alpha \leqslant 1$, $0 < \xi < \theta$

For validation purposes, the simulated hourly rainfall will be divided into two non-overlapping periods of i) 1975 to 1995 and ii) 1996 to 2015. 1975 to 1995 will be used as

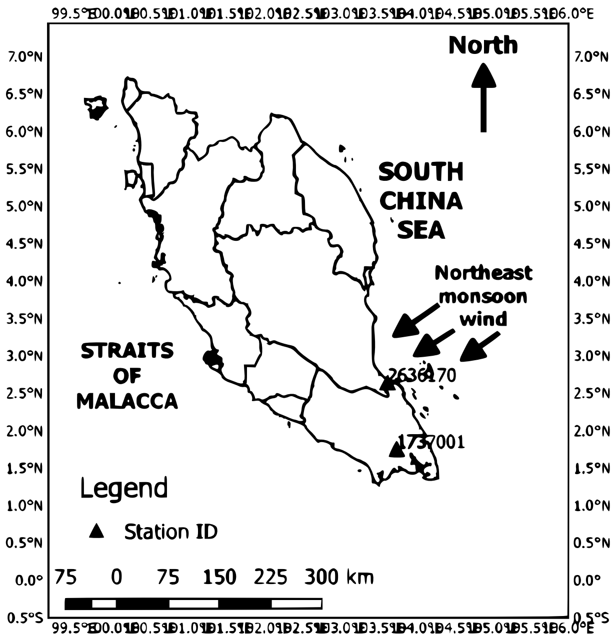


Figure 1: Location of rainfall stations

Table 1: Name of stations with station ID, latitude (Lat) and longitude (Lon)

Station ID	Name of Station	Lat(^oC)	Lon(^oC)
1737001	Sek. Men. Bukit Besar, Kota Tinggi Johor	1.76	103.74
2636170	Stor JPS Endau, Johor	2.65	103.62

Table 2: Rainfall parameters of the NSRP model.

Parameter	Definition
λ	Mean storm origin arrivals (h)
β	Mean waiting time for cell origins after the origin of the storm (h)
η	Mean duration of the cell (h)
μ_c	Mean number of cell per storm [-]
α	Mixing probability
ξ	Scale parameter (light rain)
θ	Scale parameter (heavy rain)

the reference period where the multiplicative factor is calculated based on the simulation output and the high resolution observational data. The changing factors will then be used to correct the biases of the simulation output from 1996 to 2015. The revised hourly rainfall is then compared to the observation from the identical period of 1975 to 1995. Generations of rainfall series with respect to extreme rainfall and dry/wet spell lengths at each rainfall station are conducted using the identified distribution.

III. Results and Discussion

The simulated statistical properties of rainfall i.e. mean (μ), variance (σ^2), lag-1 autocorrelation ($\rho(h)$), skewness ($\kappa(h)$), frequency of non-precipitation ($\Phi(h)$), and transition probability wet-wet ($\nu(h)$) at 1-hour aggregation pe-

Table 3: Statistical properties at 1-hour aggregation period for Station 1737001.

Month		μ	σ^2	$\rho(h)$	$\kappa(h)$	$\Phi(h)$	$\nu(h)$
Jan	Obs	0.21	1.83	0.53	13.32	0.91	0.75
	Sim	0.20	1.75	0.55	12.44	0.93	0.62
Feb	Obs	0.15	1.68	0.45	16.29	0.94	0.76
	Sim	0.15	1.57	0.50	24.47	0.94	0.48
Mar	Obs	0.23	3.15	0.44	13.98	0.91	0.75
	Sim	0.23	3.15	0.41	16.71	0.93	0.48
Apr	Obs	0.23	3.31	0.33	14.44	0.91	0.74
	Sim	0.25	3.77	0.29	15.35	0.95	0.55
May	Obs	0.21	3.06	0.29	17.05	0.91	0.74
	Sim	0.20	3.96	0.15	22.66	0.95	0.23
Jun	Obs	0.16	2.15	0.29	17.92	0.93	0.71
	Sim	0.15	2.26	0.35	19.80	0.96	0.40
Jul	Obs	0.19	2.94	0.38	16.81	0.93	0.72
	Sim	0.18	3.62	0.38	21.53	0.96	0.33
Aug	Obs	0.22	3.79	0.30	22.95	0.92	0.74
	Sim	0.22	5.92	0.37	32.79	0.96	0.36
Sep	Obs	0.23	3.08	0.30	13.67	0.92	0.69
	Sim	0.19	3.91	0.31	24.37	0.96	0.30
Oct	Obs	0.25	3.46	0.35	14.14	0.89	0.77
	Sim	0.25	4.53	0.27	21.78	0.94	0.38
Nov	Obs	0.28	7.00	0.18	52.32	0.88	0.73
	Sim	0.34	12.37	0.19	21.22	0.96	0.29
Dec	Obs	0.32	3.34	0.47	13.61	0.86	0.77
	Sim	0.34	3.80	0.50	11.46	0.89	0.56

riod are compared. Results in Figure 2 and Tables 3 and 4 show that μ, σ^2, $\rho(h)$ and $\kappa(h)$ seem to be well simulated. The overall observed monthly statistics show that the rainfall variability in the studied stations is slightly different where the μ ranged from 0.1 mm/h to 0.3 mm/h and 0.1 mm/h to 0.8 mm/h, respectively. This is probably due to geographical factor whereby station 2636170 is located at the eastern part of Peninsular Malaysia. The eastern part is more vulnerable to the northeast monsoon wind which brings heavier rainfall to the region. Meanwhile, the σ^2 for station 1737001 ranged from 1.68 mm/h to 7.00 mm/h and the σ^2 for station 2636170 ranged from 1.85 mm/h to 14.05 mm/h. High range of variance is found at station 2636170 with 12.2 mm/h (14.05-1.85=12.2 mm/h) as compared to station 1737001 with 5.32 mm/h (7.00-1.68=5.32 mm/h) due to high variability of monthly rainfall in station 2636170 as compared to station 1737001. The $\rho(h)$ for both stations seem to be fairly similar with the highest is observed at station 2636170 with a value of 0.61 and the lowest is observed at station 1737001 with a value of 0.1. This shows that both stations have positive serial correlations. As for the $\kappa(h)$, both stations are positively skewed and the skewness values are very much the same. However, the values of $\Phi(h)$ and $\nu(h)$ at stations 1737001 and 2636170 ranged between 0.7 and 0.9 and between 0.4 and 0.7, respectively.

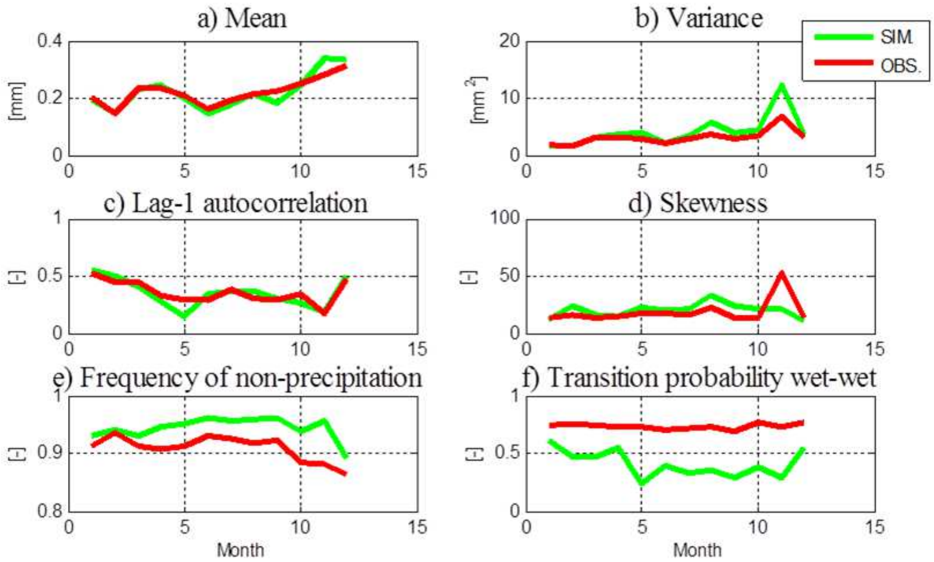
The simulated result for each month is then being summarize into a boxplot. Graphs as

Table 4: Statistical properties at 1-hour aggregation period for Station 2636170.

Month		μ	σ^2	$\rho(h)$	$\kappa(h)$	$\Phi(h)$	$\nu(h)$
Jan	Obs	0.48	6.36	0.61	9.98	0.87	0.74
	Sim	0.47	5.57	0.62	9.19	0.88	0.68
Feb	Obs	0.26	4.49	0.53	15.35	0.93	0.71
	Sim	0.25	4.16	0.57	15.34	0.95	0.60
Mar	Obs	0.25	3.61	0.45	13.68	0.92	0.72
	Sim	0.23	2.21	0.65	11.02	0.94	0.64
Apr	Obs	0.15	1.85	0.29	16.57	0.941	0.69
	Sim	0.14	1.25	0.25	15.46	0.943	0.39
May	Obs	0.16	2.32	0.28	17.76	0.949	0.65
	Sim	0.16	3.12	0.19	27.17	0.956	0.25
Jun	Obs	0.16	2.33	0.29	17.25	0.940	0.70
	Sim	0.15	1.95	0.20	18.77	0.953	0.29
Jul	Obs	0.18	3.05	0.27	16.77	0.937	0.71
	Sim	0.19	9.45	0.12	42.34	0.974	0.08
Aug	Obs	0.18	2.64	0.28	16.87	0.937	0.68
	Sim	0.17	2.87	0.30	23.72	0.952	0.29
Sep	Obs	0.19	2.77	0.33	16.25	0.931	0.69
	Sim	0.19	2.63	0.30	17.49	0.945	0.36
Oct	Obs	0.24	3.18	0.32	14.03	0.903	0.74
	Sim	0.21	2.34	0.27	17.68	0.926	0.36
Nov	Obs	0.47	5.98	0.44	9.92	0.833	0.74
	Sim	0.49	5.74	0.44	9.16	0.858	0.54
Dec	Obs	0.89	14.05	0.60	8.53	0.774	0.79
	Sim	0.95	13.16	0.70	7.73	0.785	0.72

given in Figure 3, show the simulated series (green boxplot) against the observed series (red line graph). Generally, the performance of the model is quite good in mimicking the observed rainfall series with the mean of rainfall is well simulated. As seen in the figure, the peak rainfall amount for both stations occur in December, followed by November. It is interesting to note that these months correspond to the northeast monsoon season which takes place from November to February. The result is also consistent with Wong et al. (2016) where the study delineates this region based on the characteristics of rainfall. However, the maximum amount of monthly mean rainfall for station 2636170 may reach up to 1000 mm/month whereas for station 1737001, the value only reaches up to 350 mm/month. The study concluded that the southeastern region of the peninsular where station 2636170 is located, experiences rainfall peak in December and maintains high amount of rainfall in January. Moreover, the relatively flat landscape of the southeastern region like station 1737001, resulting in reduced spatial variability hence smaller amount of monthly rainfall received. It is also can be seen that during the southwest monsoon season which takes place from May to August, both stations receive less rainfall. This shows that the northeast monsoon influence is stronger and contributes more rainfall over Johor than the southwest monsoon. The rainfall amount during the inter-monsoon season/transition period (i.e. March/April

(a) Station 1737001



(b) Station 2636170

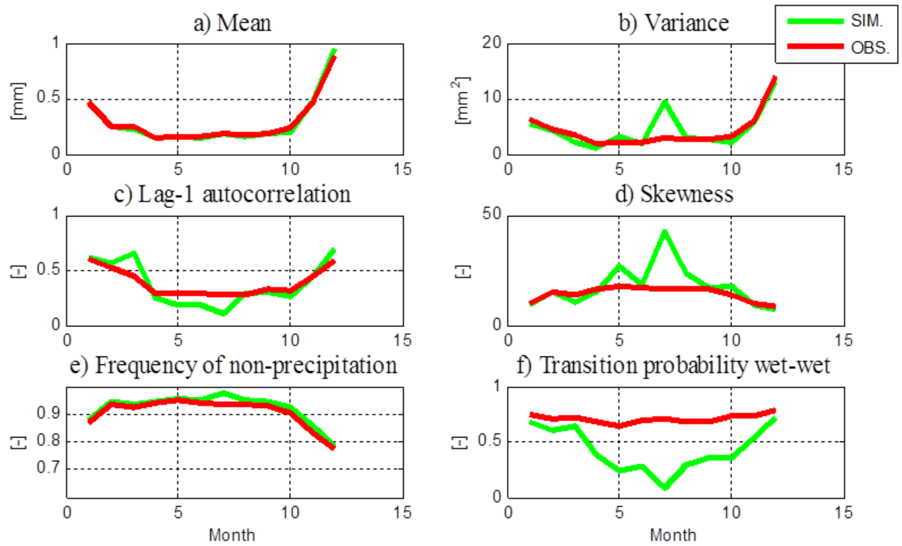
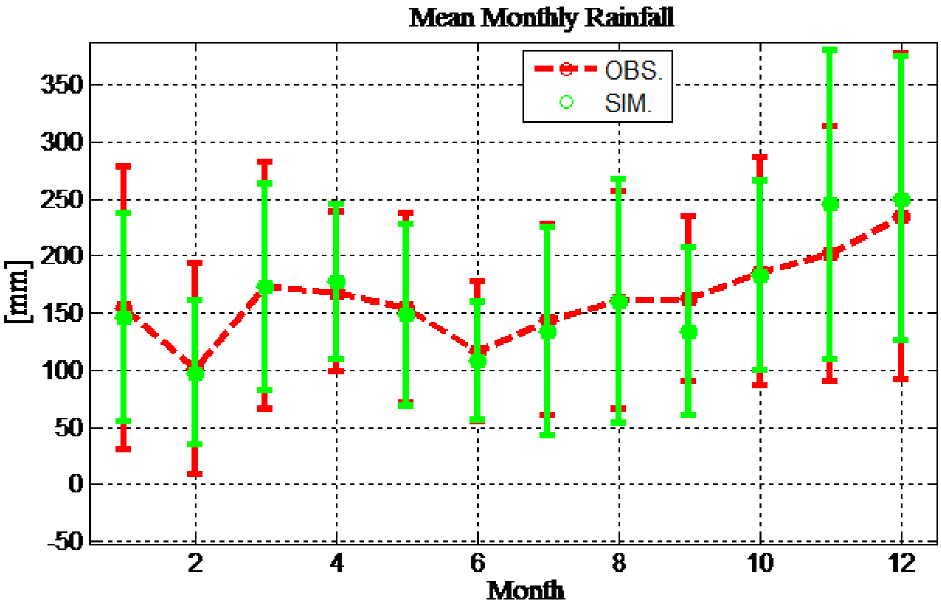


Figure 2: Comparison between observed (red) and simulated (green) mean monthly statistics of hourly rainfall for (a) Station 1737001 and (b) Station 2636170.

and September/October) are influenced by the monsoon seasons (Loo et al. (2015)).

Figure 4 reveals the simulation result of extreme rainfall and wet/dry spell lengths for both of the stations. Both hourly and 24-hour extreme rainfall seem to be well captured by the model. Meanwhile, dry and wet spell lengths are slightly underestimated. Similarly, wet spell length seems is also underestimated in the simulation. As referred to Figure 4, in the 30-year return period, there is not much difference in the range of hourly and 24 hour extreme rainfall amount for both stations which range from 200 to 500 mm.

(a) Station 1737001



(b) Station 2636170

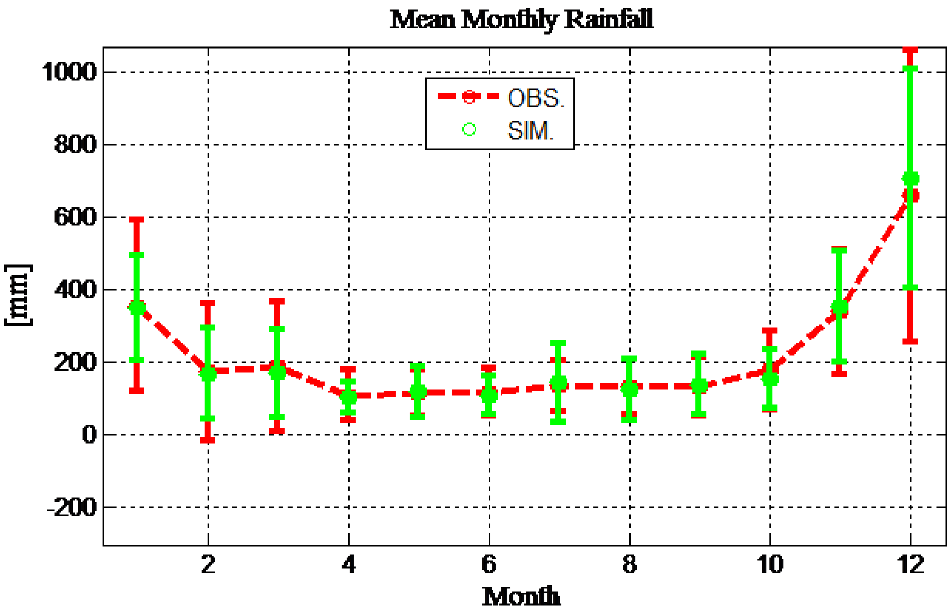
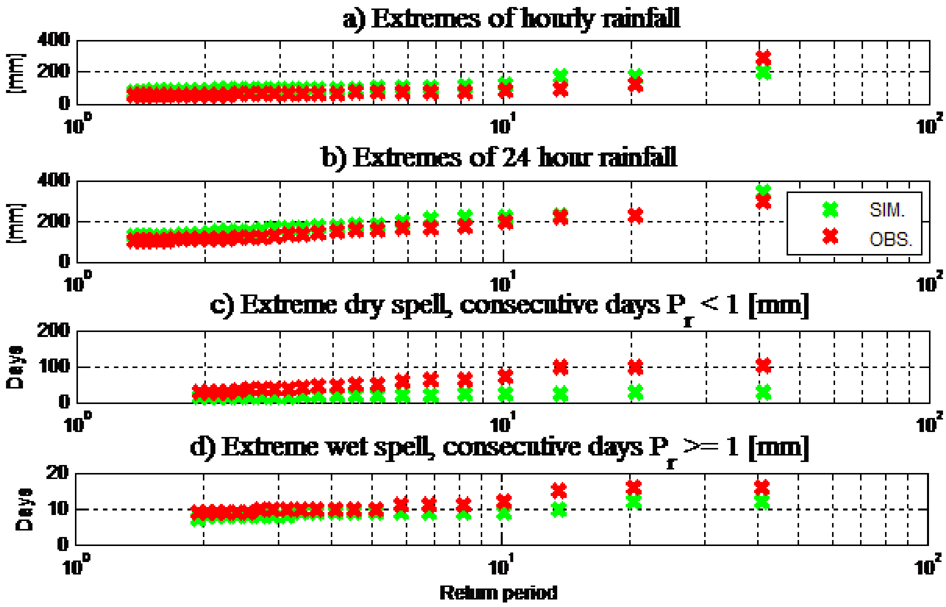


Figure 3: Monthly rainfall at each station.

IV. Conclusion

Overall, the AWE-GEN model is proven to be capable of replicating the monthly rainfall series for 2 stations in Johor with Mixed Exponential distribution representing the rainfall intensity. The model is able to capture the main characteristics of rainfall distribution in Johor very well. Generally, the seasonal wind gives significant influence to the mean rainfall amount received by each station. Station located towards the eastern part of Peninsular Malaysia is more prone to northeast monsoon wind and receives more rainfall compared to station located towards the middle part of Peninsular Malaysia which is less prone to the

(a) Station 1737001



(b) Station 2636170

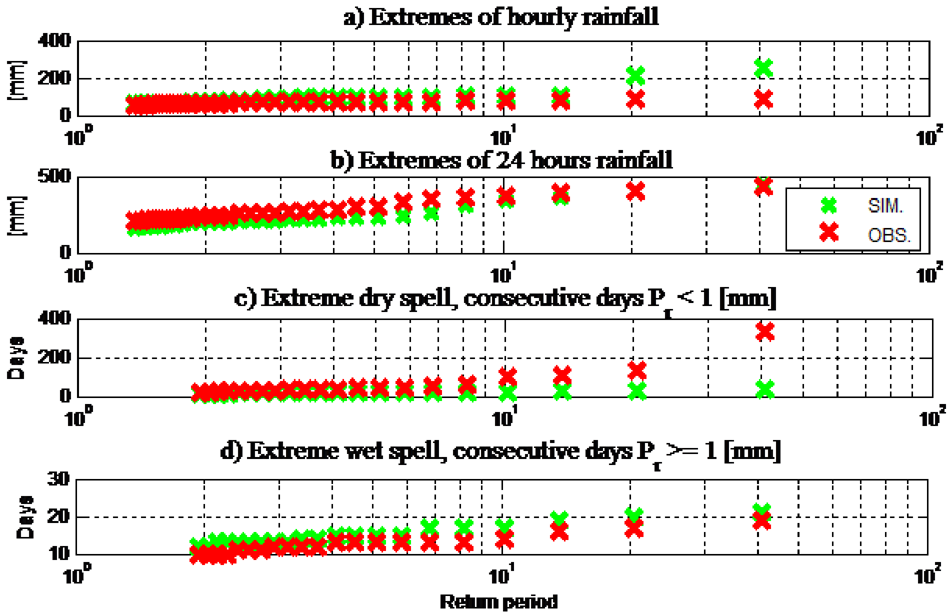


Figure 4: Extremes rainfall (a) hourly (b) 24 hour and extremes spell length (c) dry consecutive days and (d) wet consecutive days.

northeast monsoon wind. The successful development of this model could be beneficial in addressing issues such as insufficiency of rainfall data at rainfall stations. In addition, the model could be employed to generate data as input to various hydrological models.

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